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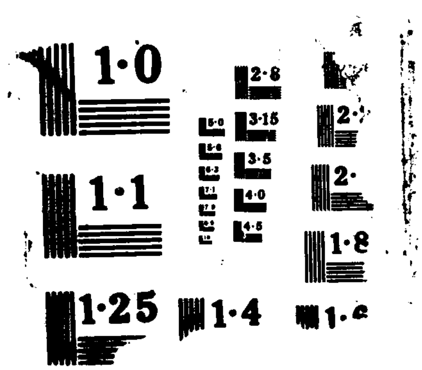
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Report No. 6771

AD-A194 930

Human Plausible Reasoning

Allan Collins, Mark Burstein, and Michelle Baker

January 1988

Approved for publication; distribution unlimited

SECURITY CLASSIFICATION OF THIS PAGE (When Data Entered)

REPORT DOCUMENTATION PAGE

READ INSTRUCTIONS BEFORE COMPLETING FORM

1. REPORT NUMBER: BBN Report No. 6771	2. GOVT ACCESSION NO.
3. RECIPIENT'S CATALOG NUMBER	
4. TITLE (and Subtitle): Human Plausible Reasoning	5. TYPE OF REPORT & PERIOD COVERED: Annual Interim Report October 1986-September 1987
	6. PERFORMING ORG. REPORT NUMBER
7. AUTHOR(s): Allan Collins, Mark Burstein, and Michelle Baker	8. CONTRACT OR GRANT NUMBER(s): MDA903-85-C-0411
9. PERFORMING ORGANIZATION NAME AND ADDRESS: BBN Laboratories Incorporated, 10 Moulton Street, Cambridge, MA 02238	10. PROGRAM ELEMENT, PROJECT, TASK AREA & WORK UNIT NUMBERS: 2Q161102B74F
11. CONTROLLING OFFICE NAME AND ADDRESS: US Army Research Institute for the Behavioral and Social Sciences, 5001 Eisenhower Avenue, Alexandria, VA 22333-5600	12. REPORT DATE: January 1988
	13. NUMBER OF PAGES: 11
14. MONITORING AGENCY NAME & ADDRESS (if different from Controlling Office)	15. SECURITY CLASS. (of this report): Unclassified
	15a. DECLASSIFICATION/DOWNGRADING SCHEDULE

16. DISTRIBUTION STATEMENT (of this Report)

Approved for public release; distribution unlimited.

17. DISTRIBUTION STATEMENT (of the abstract entered in Block 20, if different from Report)

18. SUPPLEMENTARY NOTES

Contracting officer's representative was Judith Orasanu.

19. KEY WORDS (Continue on reverse side if necessary and identify by block number)

reasoning
artificial intelligence
similarity
analogy

20. ABSTRACT (Continue on reverse side if necessary and identify by block number)

This report describes the current state of implementation of a cognitive computer model of human plausible reasoning, based on the theory of plausible reasoning described by Collins and Michalski. Our goal is to use the simulation as a means of testing and refining the theory. This requires developing appropriate memory organization and search techniques to support of this style of inference, finding ways to estimate similarity in specific contexts and investigating ways of combining the sometimes

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Human Plausible Reasoning
Executive Summary

During the second year of the contract our work centered in four areas:

1. We completed a computer model embodying the theory of plausible reasoning developed in the paper by Collins and Michalski entitled "The Logic of Plausible Reasoning: A Core Theory" to be published in Cognitive Science. The simulation model was developed by Michelle Baker and Mark Burstein, and is described in detail in the rest of this report.

2. We wrote a paper describing the simulation model entitled "Implementing a Theory of Human Plausible Reasoning" by Michelle Baker, Mark Burstein, and Allan Collins, which was presented at IJCAI in Milan Italy, and appears in the Conference Proceedings of IJCAI-10, 1987. This paper constitutes the bulk of this report.

3. We constructed two small data bases, one on grain growing (shown in Table 1 below) and one in economics. These were implemented in the system in order to test out what plausible inferences the system draws given incomplete information about a given domain. In addition to the kind of data shown in Table 1, various mutual dependencies (e.g. precipitation $\wedge$ irrigation <--> water supply) were also included in the data base in order to constrain the plausible inferences drawn.

4. We ran four expert reasoners with little knowledge of geography in an experiment using the grain growing data base shown in Table 1 below. Subjects were asked to specify first what mutual dependencies between the variables shown they knew about a priori. Then they were asked to try to guess the values of the unspecified variables and to explain the basis of their reasoning. Their plausible inferences will be directly compared to the plausible inferences made by the computer model over the same data, and where there are systematic differences the computer model will be refined accordingly.

Table 1

Incomplete Data Base on Grain Growing in Different Countries

12 x 9	Climate	Water Supply	Grain Grown	Has River?	Precip-itation	Season Description	Soil Type	Temperature Range	Terrain
Afghanistan	?	?	NONE	?	?	?	Brown Grey	Hot Very Hot	Mountains
Angola	?	Moderate Abundant	Corn	YES	Abundant	Summer Rain	Dark Brown Grey	Hot	?
Egypt	Dry Climate	Moderate (Irrigated)	Wheat	YES	Very Light	?	Grey	Very Hot	Plains
Florida	Subtropical Humid Trop.	?	Corn	?	Moderate Abundant	Mild Winter Long Summer Even Rain	?	?	Lowlands Plains
Iran	Semi-Arid Mediteranean	?	?	NO	Light	Winter Rain	Grey	?	?
Italy	Mediteranean	Moderate	?	YES	?	Mild Winter Hot Summer Winter Rain	Complex Red-Yellow	Mild Hot	Mountains Plains
Java	Humid Tropics	?	Rice Corn	NO	Abundant Very Wet	No Winter Even Rainfall	?	Hot	Mountains Lowlands
Louisiana	Subtropical	Abundant	?	YES	?	Mild Winter Long Summer Even Rainfall	Red-Yellow Black	?	Lowlands Plains
Peru	Highland Arid	Moderate (Irrigated)	Corn Rice	?	Very Light Light	Summer Rain	Complex	?	Mountains
Saskatchewan	Dry Climate	?	Wheat Oats,Rye	YES	Light	Winter Rain	Dark Brown Brown Complex	Cool Mild	Plateau
Upper Volta	?	Abundant	Rice Millet	YES	Very Wet	?	?	Hot Very Hot	Lowlands Plains
West Indies	Humid Tropics	Abundant	Rice Corn	NO	Abundant Very Wet	No Winter Even Rainfall	Red-Yellow	Hot	?

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Implementing a Model of Human Plausible Reasoning

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Abstract

This paper describes the current state of implementation of a cognitive computer model of *human plausible reasoning*, based on the theory of plausible reasoning described by Collins and Michalski. Our goal is to use the simulation as a means of testing and refining the theory. This requires developing appropriate memory organization and search techniques to support of this style of inference, finding ways to estimate similarity in specific contexts and investigating ways of combining the sometimes contradictory conclusions reached when inferences of different types are used to answer questions. Keywords:

> Science Track: Cognitive Modelling, Artificial intelligence, Similarity, Analogy.

[1] This work was sponsored by ARI under Contract number MDA903-85-C-0411.

1. INTRODUCTION

Over the last 15 years, Collins and his colleagues (Carbonell and Collins, 1973, Collins et al., 1975, Collins,1978a, Collins,1978b)have collected and categorized a wide variety of human plausible inferences made from incomplete and inconsistent information. This work led to the development of a partial theory of plausible inference (Collins and Michalski, in press) for situations where the most appropriate or specific information was not available. This paper describes some current work in progress, the development of a computer simulation of a portion of that theory. Our goal is to use the simulation as a means of testing and refining the theory.

The popularity of expert systems has generated great interest in developing techniques to reason with uncertain information. To date, research on reasoning under uncertainty has emphasized the role of statistical theory. (Pearl, 1986, Duda et al., 1976). Unfortunately, in most real-world problems neither the data nor the inference rules themselves are known to apply with precise certainties. Methods of combining uncertain evidence from multiple sources are also often required. With the exception of Cohen (Cohen, 1985), it has usually been assumed that the appropriate certainty parameters and the methods of combination were independent of the type of inference performed. Furthermore, these techniques usually require some form of closed world assumption for correct interpretation. Unfortunately, in most real-world situations, the available information is incomplete as well as uncertain. People deal with this problem continually, and quite effectively, using techniques for reasoning by similarity, reasoning from negative information, and reasoning from their own lack of knowledge about particulars (e.g., "I would know it if Ronald Reagan was 10 feet tall.") It is these kinds of inferences that we seek to model.

Collins' theory of plausible reasoning is based on a corpus of people's answers to everyday questions (Collins,1978b). In general, he found that these answers had the following characteristics:

1. There are usually several different inference types used to answer any question.
2. The same inference types recur in many different answers.
3. People weigh different evidence (and different kinds of evidence) they find that bears on a question.
4. People are more or less certain depending on the certainty of their information, the certainty of the inferences used, and on whether different inferences lead to the same or opposite conclusions.

Also apparent from the protocols is that subjects faced with answering a question for which they have no specific knowledge launch a search for relevant information that they do have. As relevant pieces of information are found (or are found to be missing), they trigger particular types of inferences. The type of inference applied is determined by the relation between the information found and the question asked. For example, when a tutor was asked whether they grow coffee in the Llanos region of Colombia, he responded:

> I don't think that the savanna is used for growing coffee. The trouble is the savanna has a rainy season and you can't count on rain in general. But I don't know, this area around Sao Paulo (in Brazil) is coffee region, and it is sort of getting into the savanna region there.

Initially, the tutor said no because he knew that coffee growing depends on factors like rainfall, temperature, soil, etc. and the savannas do not have the correct value on the rainfall factor. (This is called a derivation from mutual implication in the theory.) Secondly, he did not know specifically that the Llanos was used for coffee growing, and believed that he would know if it was (lack of knowledge). Later, he

backed off when he found positive evidence; i.e., that the region in Brazil was near an area where coffee was grown (a similarity transform). His final answer weighed all of these pieces of evidence together, albeit inexactly.

In the remainder of this paper, we will describe an initial implementation of one part of Collins' theory of plausible reasoning, based on examples like this one. Initially, we have concentrated on modeling the class of *functional* inferences, where the inference is based on a functional dependence such as that coffee growing depends on climate and vegetation.

The primary purpose of the system is to act as a testbed for the theory. As such, it is not designed to produce one "right" answer, but a number of plausible positive and negative inferences each of which may be a weak (or not so weak) reason for believing that the question asked could be answered in a particular way. Our goals are to demonstrate that the theory produces only plausible answers, to develop ways of searching memory for the kinds of relevant information that are needed in order to apply each inference type, and to investigate methods for combining the various kinds of evidence that are produced.

The Plausible Reasoning Simulation System (PRSS) we have developed is thus quite different from other systems that have been developed to reason with incomplete and/or uncertain information. Since it is intended to simulate human reasoning, it generates multiple proofs of both the truth and the falsity of a given proposition. The types of inferences made depend on the particular information found in memory, and the nature of their relevance to the question asked. Finally, the certainty of the overall conclusions reached depends on both the certainty of the evidence and the types of inferences used.

2. AN EXAMPLE

To give a sense of the behavior of the simulation system, consider how it behaves when asked a question like "Does coffee grow in Llanos?".

```
(? crop :of llanos := coffee)

NO DIRECT EVIDENCE FOUND.

TRYING NEGATIVE IMPLICATION FROM:
    CROP = COFFEE ===> RAINFALL = HIGH  (certainty .8)

    Since HIGH is not a known value for RAINFALL(LLANOS),
      and set of values for RAINFALL(LLANOS) is CLOSED.
    Conclude that COFFEE is not a value for CROP(LLANOS)
         with MEDIUM certainty.

TRYING ARGUMENT BASED DEPENDENCY TRANSFORMS....
    LLANOS and SAO-PAULO match on CLIMATE. (sim = 0.8)
    LLANOS and SAO-PAULO match on VEGETATION. (sim = 0.6)

    Using a SIM transform:
    Since CLIMATE and VEGETATION  <===> CROP
    and SAO-PAULO is similar to LLANOS with respect to CLIMATE
           and VEGETATION.  (sim = 0.7)
    and CROP(SAO-PAULO) = COFFEE
    Conclude that CROP(LLANOS) = COFFEE is TRUE with MEDIUM certainty.

Evidence is evenly mixed.  I cannot make a judgement.
```

For this example, PRSS finds two kinds of evidence. First, it reasons from the implication that coffee growing requires heavy rainfall, and from the fact that it does not believe the Llanos to have heavy rainfall, that the Llanos is not a coffee growing region. This conclusion is given medium certainty primarily because of the certainty of the implication. Secondly, it finds that the SAO-PAULO region does have coffee as a crop and matches Llanos on CLIMATE and VEGETATION, two variables involved in a mutual dependency with CROP. Since the evidence is evenly divided, no final conclusion is reached.

3. SYSTEM OVERVIEW

Unlike an expert system, which must generate a solution, PRSS tries both to verify and disconfirm each proposition that it is given as an input question. Some examples of the kinds of queries the system may receive as input are:

```
(? CLIMATE :OF ENGLAND := TEMPERATE)
(? FLOWER-TYPE :OF HOLLAND := ROSE)
(? WATER-REQUIREMENT :OF ROSE := HIGH).
```

The system responds to each query with a determination of whether the statement is TRUE or FALSE along with an estimate of the certainty of its answer and an explanation of its reasoning. When presented with a query the system first checks whether it has the answer stored directly. If so, the answer is returned along with the certainty that was recorded at the same time the fact was recorded. If it does not have the fact stored it attempts to use every plausible inference for which it has adequate information and explains what it is doing as it performs each inference. The evidence from each plausible inference is then weighed together to generate a final guess of TRUE or FALSE along with the estimated certainty of that guess.

In general, people use many different, possibly independent, arguments to convince themselves of the truth or falsity of a proposition. It is a bit like using a theorem prover that returns every possible proof. Unlike Bayesian inference networks (Pearl, 1986), which can be viewed as combining probabilistic evidence from multiple proofs to verify the truth of a proposition, our system tries to prove both the truth and, separately, the falsity of a proposition in as many ways as are possible given the information available.

Each inference made by PRSS is like a proof in that it may require backchaining to generate information necessary for the top level inference. Each top level inference (i.e. proof based on uncertain information) becomes a separate bit of evidence. Proofs that the query proposition are true are gathered together as evidence for the proposition and proofs of falsity are pooled as evidence against the proposition. Each bit of evidence has a certainty parameter that has been derived by combining the certainty parameters of the stored propositions used and parameters that measure the goodness of matches required in the applications of inference rules. The final judgment and the system's certainty of that judgment depend on the certainties of the evidence and on how contradictory the evidence was.

4. THE KNOWLEDGE BASE

We have tried to model the system on the behavior of people when generating functional inferences. This has required a highly redundant, crossreferenced memory organization. The knowledge representation system we developed for this purpose provides mechanisms for automatic crossreference of every input proposition, allowing for redundancies in set/subset relations, and multiple indexing of declarative inference rules. Collins and Michalski's theory assumes that inferences are made when relevant information is found by a parallel search for information associated with the argument and the referent of the query. While our current simulation does not do this directly, we have implemented a set of specialized search routines that collect all information potentially useful for (possibly several of) the inference types so far implemented.

PRSS has a database consisting of propositional knowledge and functional relations (implications and mutual dependencies), organized in a multiply-indexed semantic network. In the existing implementation each proposition is a binary relation. We are currently working on extending the representation to include structured objects and n-ary relations.

Collins and Michalski (in press) identified four different certainty parameters associated with the propositions or declarative knowledge in this network. Two parameters, ***certainty*** and ***frequency*** are associated with each proposition in the knowledge base. For example, we might have

```
CLIMATE(AFRICA) = TEMPERATE,  frequency = .3,  certainty = .9
CLIMATE(AFRICA) = TROPICAL,   frequency = .5,  certainty = HIGH .
```

Following the notation of Collins and Michalski *(in press)*, we call the predicate a *descriptor*, which, together with its argument (here, AFRICA) forms a *term*. The predicate CLIMATE is the descriptor, mapping its *argument* (a place) to various *referents* (values for climates). The *certainty* parameter is a measure of degree of certainty that a statement is believed to be true. The *frequency* parameter[2] measures the estimated proportion of the referent out of all possible referents for that descriptor and argument. The example above represents the belief that 30% of AFRICA is temperate and 50% is tropical.[3]

In addition to certainty, a likelihood parameter is attached to each implication and dependency. For example we might have the dependency,

```
For all Places p,
   TEMPERATURE(p) <===> LATTITUDE(p)
         certainty = .9 ,likelihood = HIGH.
```

where the likelihood is intended to be a measure of the conditional probability of the right-hand side given the left hand side. For an implication like the one below, it is a measure of the likelihood that the right hand side of the implication is in the given range when the left hand side is in its specified range.

```
For all Places p,
   GRAIN(p) = rice ===> rainfall(p) = heavy
```

---

[2]Corresponding to the all/some distinction in logic.

[3]At present we assume that potential ambiguities associated with the meaning of the frequency parameter - e.g. does it refer to space or time - are accounted for by consistent interpretation by the user.

```
certainty = .9, likelihood = HIGH.
```

The fourth type of certainty parameter stored with the declarative knowledge of the system is ***dominance***. A dominance parameter is associated with every set/subset link in the system. It measures the proportion of elements in the subset out of all elements in the set. For example, PART-OF(ENGLAND) = SURREY would have low dominance, since Surrey is a small part of England.

5. MULTIPLE TYPES OF INFERENCE

The current version of PRSS implements three basic types of functional inferences on statements retreived from its memory, depending on the kind of dependency found and the resulting kind of contextually-based similarity match required. The three types are *functional analogies*, which are based mutual dependencies between descriptors, *implication inferences*, and *set/subset* inferences.

In the example below, we show how the system is able to construct three separate "proofs" that the climate of England is temperate. Given the data in memory provided for this example, the system is unable to construct a single proof that the climate of England is not temperate.

(? climate :of england := temperate)

```
Using an Inheritance transform:
    Since ENGLAND = PART-OF(EUROPE)   (dom = LOW)
    And EUROPE has CLIMATE = TEMPERATE   (certainty = HIGH)
    Conclude that CLIMATE(ENGLAND) = TEMPERATE is TRUE with MED certainty.

Using an Implication transform:
    Since LATITUDE = SECOND-QUAD or THIRD-QUAD   ===> CLIMATE = TEMPERATE
    and LATITUDE(ENGLAND) = THIRD-QUAD
    Conclude that CLIMATE(ENGLAND) = TEMPERATE is TRUE with MEDIUM certainty.

TRYING ARGUMENT BASED DEPENDENCY TRANSFORMS....
    Using a SIM transform I reason:
    Since LATITUDE <===> CLIMATE
    and HOLLAND is similar to ENGLAND with respect to LATITUDE.   (sim = 1.0)
    and CLIMATE(HOLLAND) = TEMPERATE.
    Conclude that CLIMATE(ENGLAND) = TEMPERATE is TRUE with MEDIUM certainty.

TRYING REFERENT BASED DEPENDENCY TRANSFORMS.....
      Insufficient Information Available.

I conclude CLIMATE(ENGLAND) = TEMPERATE. (certainty = HIGH).
```

One general class of functional inference is called ***statement transforms*** (Collins and Michalski, in press). This type of inference requires a declarative rule called a ***dependency***. In the example above, an analogy is made between England and Holland. The system is aware of a general relationship that the climate of a place is dependent upon the latitude of a place. In order to determine whether a specific relation exists between a latitude in the third-quad (45-67.5 deg.) and a temperate climate the system must find an instance analogous to England which is known to have a temperate climate. Holland is such an instance. Since Holland and England have the same latitude the system can conclude that England can have a temperate climate as well.

Argument-based Transforms

```
GEN:  flower-type(Europe)={daffodils, roses...}

SPEC: flower-type(Surrey)={daffodils, roses...}

SIM:  flower-type(Holland)={daffodils, roses...}

DIS:  flower-type(Brazil)≠{daffodils, roses...}
```

Reference-based Transforms

```
GEN:  flower-type(England)={temperate flowers...}

SPEC: flower-type(England)={yellow-roses...}

SIM:  flower-type(England)={peonies...}

DIS:  flower-type(England)≠{bougainvillea...}
```

Figure 5-1: Eight Transforms on "flower-type(England)={Daffodils, roses...}

Within the class of statement transforms, Collins and Michalski (in press) describe eight different kinds of *transforms*, four *argument-based* transforms, and four *reference-based* transforms. The eight inference transforms were derived by considering concepts related to the ones mentioned in the question asked, where the relationship could be any of *generalization, specialization, similarity, and dissimilarity*. Each of these *operators* could be applied to either the argument or the referent in the question statement, giving the total of eight specific transforms. Figure 5-1 gives an example of each of the eight transforms for the statement FLOWER-TYPE(ENGLAND)={daffodils, roses...}. The overall certainty of an inference based on one of these transforms depends on the degree of similarity or typicality of the concepts related, *as compared along the dimensions specified in the dependency used*, and the degree of certainty of the dependency itself.

The dependency used in the example above can be described in the predicate calculus as,

$$\forall\ p1,p2,l,c\quad \mathrm{PLACE}(p1) \wedge \mathrm{PLACE}(p2) \wedge \mathrm{LATITUDE}(p1,l) \wedge \mathrm{LATITUDE}(p2,l) \wedge \mathrm{CLIMATE}(p2,c) \Longrightarrow \mathrm{CLIMATE}(p1,c)$$

i.e. if two places match on latitude then they will match on climate.

The simplest type of functional inference is based on a type of declarative inference rule called an ***implication***. Implication inferences can be used to infer values for properties on the basis of other properties of the same concept. Since the precise relation is completely specified in an implication, an analogous instance is not required for its application. The implication used in the example above can be expressed using the predicate calculus as,

$$\forall\ x,\quad \mathrm{PLACE}(x) \wedge \mathrm{LATITUDE}(x,\mathrm{THIRD\text{-}QUAD}) \Longrightarrow \mathrm{CLIMATE}(x,\mathrm{TEMPERATE})$$

i.e. if the latitude of a place is third-quad then the climate of that place is temperate.

In the next example, the system first generates an argument-based statement transform using a dependency whose consequent is the queried descriptor, FLOWER-TYPE. It finds a place where tulips are grown (Holland) and compares that place to Venezuela on the antecedent descriptor of the dependency, CLIMATE. Since they do not match, it concludes that tulips don't grow in Venezuela. The second inference is a reference-based transform. Here, a dependency is required whose consequent is the inverse of the query descriptor FLOWER-TYPE (i.e GROWS-IN), since one needs to find a flower that grows in Venezuela and which is similar to tulips with respect to the factors that affect flower growth in a place.[4]

(? flower-type :of venezuela := tulip)

```
TRYING ARGUMENT BASED DEPENDENCY TRANSFORMS....
    Using a DIS transform I reason:
    Since CLIMATE <===> FLOWER-TYPE
    and HOLLAND is dissimilar to VENEZUELA with respect to CLIMATE.
                                                        (sim = -1.0)
    and FLOWER-TYPE(HOLLAND) = TULIP.
    Conclude that FLOWER-TYPE(VENEZUELA) = TULIP is FALSE with LOW certainty.


TRYING REFERENT BASED DEPENDENCY TRANSFORMS.....
    Using a DIS transform I reason:
    Since CLIMATE-OF <===> GROWS-IN
    and BOUGAINVILLEA is dissimilar to TULIP with respect to CLIMATE-OF.
                                                        (sim = -1.0)
    and GROWS-IN(BOUGAINVILLEA) = VENEZUELA.
    Conclude that GROWS-IN(TULIP) = VENEZUELA is FALSE with LOW certainty.

   I conclude TULIP IS NOT FLOWER-TYPE of VENEZUELA. (certainty = MED).
```

---

6. COMPUTING THE CERTAINTY OF AN INFERENCE

Each of the examples shown so far involves several types of inference, and the certainty of each inference is based on a combination of several certainty parameters and a similarity or typicality measure.

The two similarity parameters computed by the matcher are ***similarity*** and ***typicality***. At present, these two parameters measure the quality of a match and are computed in exactly the same way. The difference between them is that typicality applies when a property (properties) of a set is being matched with those of a subset and similarity is computed as the quality of a match between two subsets. In the theory, similarity (or typicality) measures the quality of the match either of a single feature or of a bundle of features.

In the current implementation we compute the similarity (or typicality) of a single feature with multiple known values by an urn model type algorithm.[5] The similarity parameter is currently computed as the

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[4]The system uses a knowledge representation in which the descriptor definitions may specify an inverse. The descriptor FLOWER-TYPE has been defined as having a domain that must be a PLACE, a range that must be a FLOWER, and an inverse named, GROWS-IN. Thus while FLOWER-TYPE maps from PLACES into the FLOWERS that grow there, GROWS-IN maps FLOWERS into the PLACES where they grow.

[5]In the future, we plan to extend the matcher to compare multiple features with multiple values.

probability that two values for a given feature, chosen at random within their frequency distributions, match or mismatch.

The certainty of each individual inference is currently computed as the minimum of all the certainty parameters and match certainties used. This includes the certainties associated with every proposition used, the certainty and the likelihood of the inference rule and similarity measure returned by the matcher.

Once the system has constructed every possible proof for a given proposition it must determine whether the proposition is true or false and estimate the certainty of its guess. Currently this is done by weighing the evidence for the proposition with the evidence against that proposition. The certainties of all of the positive conclusions are combined, and all of the negative conclusions are combined. Multiple lines of evidence in a given direction increases the certainty of the conclusion for that direction. The final judgment is the direction with the greater certainty, and the certainty of that judgement is downweighted by the certainty of the conclusion in the opposite direction.

7. CONCLUSION

This work is still in its early stages, and yet already we see a number of interesting issues that will require further study. To date, we have not run the simulation with large numbers of facts in memory, and we forsee that this will cause the number of inferences the system makes to grow exponentially. Clearly, techniques will be needed to control this growth, such as the filtering of weak and redundant inferences, the use of prototypes when many similar examples exist, and more sophistocated representations for complex dependancies and implications. We also need to develop better and more efficient techniques for similarity matching, if we are to do matches on many contextual features at once. As the model continues to develop, we will also begin a new round of protocol experiments, in order to test our model, and answer some of the questions discovered by computer modeling.

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